Leveraging Gait for People Perception

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Doctor of Philosophy

under the supervision of Dr. Alen Alempijevic and Dr. Teresa Vidal-Calleja

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Declaration of Authorship

I, Julien Claude Guy Collart, declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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UNIVERSITY OF TECHNOLOGY SYDNEY

Abstract

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In the past few years, there has been an increase in the number of robots interacting with people in public spaces. Robots and humans co-existing in an environment require an understanding of each other's intention to perform safe and optimal interactions. One of the most basic forms of intention inference consists of predicting an individual's future poses. While existing work on human tracking tends to use basic knowledge of the gait directly extracted from the lower-body that governs the spatio-temporal dynamics of the locomotion, such methods become impractical in public environments where the number of people and occlusions make it nearly impossible to see the placement of the feet and legs.

In this work, we propose a framework for people perception and intention inference in real-time which leverages the relationship between the feet and upper-body for estimating and predicting future postures and gait phases when the feet cannot be directly observed. In addition, the inputs to the framework solely use depth data, with the added benefit of being privacy-friendly.

The spatio-temporal relationship between the feet and the upper-body was exploited to design a framework for gait phase inference from shoulder pose observations. Classification of gait phases is achieved using Hierarchical Hidden Markov Models that are capable of modelling complex sequences. The experimental results confirm that the current gait phase can be estimated from shoulder poses alone.

Given that shoulder motion can be used for inferring the current gait phase, a second framework was designed to exploit the anticipatory signals contained in the upper-body motion to predict the future gait phase and posture. A Recurrent Neural Network was used to encode long-term dependencies in the sequences of poses. A custom loss function was constructed to direct the learning by incorporating the bio-mechanical constraints of human locomotion. Experimental results confirm that the motion states, postures and gait phases, can be predicted from a sequence of shoulder poses, and that the accuracy is improved by the custom loss function.

Finally, the problem of predicting an individual's future poses is addressed by transferring the learning from the second framework's model to train another classifier used to drive a dynamic motion model's internal parameters within a tracking algorithm. Experimental results confirm that the motion states predictive model can be used to boost and improve the learning of a different classifier related to human motion, so that human tracking is improved.

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Catherine Collart, née Clement

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Acronyms & Abbreviations

1D	One-Dimensional
2D	Two-Dimensional
3D	Three-Dimensional
CAS	Centre for Autonomous Systems
UTS	University of Technology Sydney
COM	Center Of Mass
COP	Center of Pressure
MAXCOP	Maximum Center Of Pressure
GI	Gait Initiation
GCY	Gait Cycle
GT	Gait Termination
GIR	Gait Initiation with Right foot first
GIL	Gait Initiation with Left foot first
GTR	Gait Termination with Right foot first
GTL	Gait Termination with Left foot first
GMM	Gaussian Mixture Model
EM	Expectation-Maximization

E-Step Expectation Step

M-Step Maximization Step

HMM Hidden Markov Model

Pr Probability

HHMM Hierarchical Hidden Markov Models

H-DBN Hierarchical Dynamic Bayesian Network

RH Right foot Heel

LH Left foot Heel

RT Right foot Toes

LT Left foot Toes

LOO Leave One Out

STA Standing

TRS Turning on the Spot

TRSR Turning on the Spot to the Right

TRSL Turning on the Spot to the Left

TRR Turning Right while walking

TRL Turning Left while walking

ReLU Rectified Linear Unit

RNN Recurrent Neural Network

LSTM Long Short-Term Memory Network

SGD Stochastic Gradient Descent

TP True Positive

TN True Negative

FP False Positive

FN False Negative

RMSE Root Mean Square Error

MOTP Multiple Objects Tracking Precision

MOTA Multiple Objects Tracking Accuracy

IR Infrared

FPS Frames Per Second

HE Head

SH Shoulders

STR Straight walk scenario

MDI Multi-direction walk scenario

SO1 Social walk scenario 1

SO2 Social walk scenario 2

ID Identity

Glossary of Terms

Autonomous	Without human intervention.
Shoulders	Trapezius muscle.
Pose	Position and orientation.
Postures	Non-forward and non-backward motion.
Gait Phases	Phases shown during locomotion.
Motion States	States describing either only the gait phases or both.
Sub-state	Internal state to a state.